Appendix 14

Verification of model transferability

Model Verification

Verification of habitat models is a complicated task that is hampered by natural variability and environmental impact. This is especially true in systems with fauna impaired by factors that were not included in physical habitat models such as temperature, predation and other impacts. In recent years several studies have conducted various types of model verification with varying results using different techniques. The most recognized method was presented by Thomas and Bovee (1993), and suggested the use of a chi-square cross-classification for this purpose. This method is very robust as it collapses the fish density data into presence and absence categories and compares the distribution of these categories within two habitat suitability classes. It is well suited for impacted streams where one can only expect to observe basic trends (Stalnaker pers. com). In this report we analyzed the data more precisely using correlation and also incorporating fish density information.

To verify the transferability of the established criteria, the fish observations during the fisheries survey were compared with the habitat predictions at the same locations. First we conducted chi-square classification for the predicted suitable and optimal habitat classes using every observation. Subsequently the average fish density observed in surveyed HMUs was plotted against habitat suitability calculated for this HMU. The regression analysis was used to determine if the habitat quality predictions corresponded with fish distribution.

For the Upper Souhegan species selected to compose generic resident adult fish (GRAF) consisted of longnose dace, blacknose dace, common shiner, fallfish and white sucker. The slimy sculpin, Atlantic salmon, brook trout, mussels and odonates created the special interest fish and invertebrates (SIFI) group. For the Lower Souhegan the same species served as GRAF, but slimy sculpin was not included in SIFI.

Verification of transferability by electrofishing.

Flow conditions at the time of each electro-fished grid sampling were compared to the closest HMU mapping survey. The depth and velocity data and HMU characteristics for these corresponding HMUs were then used to calculate the suitability probabilities for each fish species in this analysis. In the first step the presence or absence of particular species were compared with the predicted probabilities and habitat quality classes for the same species. The chi-square cross-classification provides highly significant results (p=0) and documents that overall the model correctly separates areas of higher suitability. As presented in the Figure 1 there were a large number of grids in suitable and optimal areas where no fish could be found, which further supports low fish density observations. However, among the grids where fish were captured, significantly more were in optimal habitats.

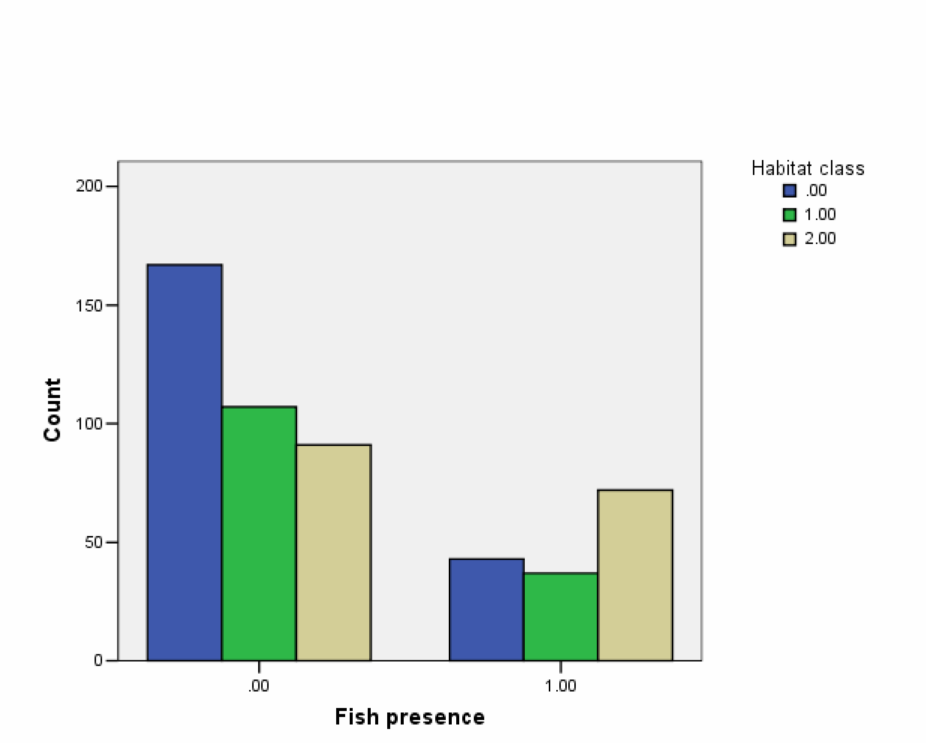

Figure 1: The number of grids where fish were present (1) in three habitat suitability categories: unsuitable (0), suitable but not optimal (1), optimal (2).

Predicted suitability was plotted against caught fish densities for the species: blacknose dace (BND), common shiner (CS), fallfish (FF), longnose dace (LND), and white sucker (WS). The graphs shown below include all surveyed HMU's that were fished using our established electro-fishing technique.

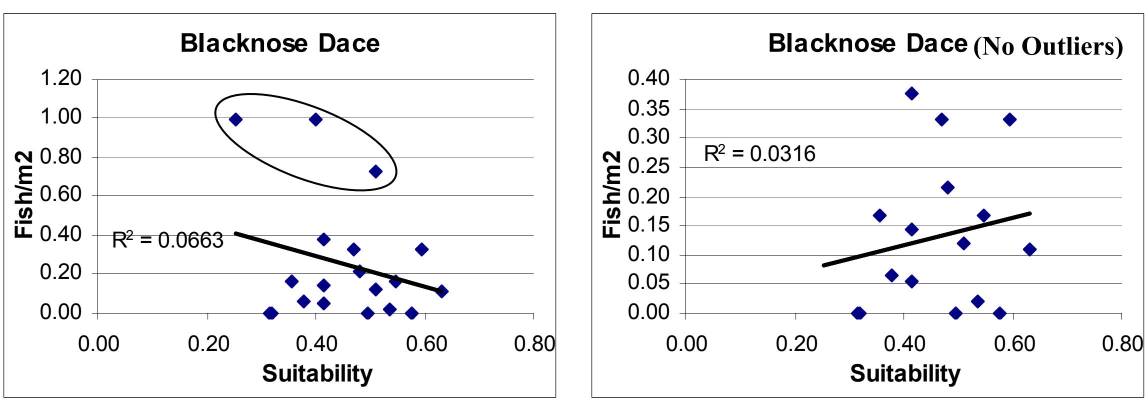

Figure 2: Predicted suitability versus fish density for blacknose dace including all observations (A) and with the removal of outliers (B).

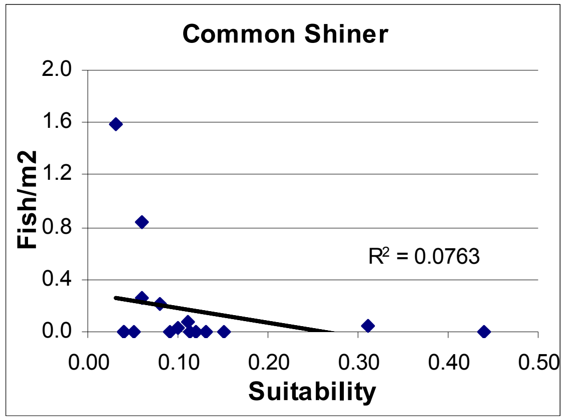

Figure 3: Predicted suitability versus fish density for common shiner.

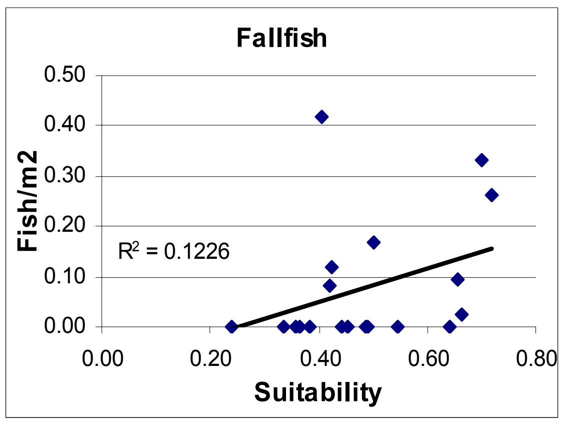

Figure 4: Predicted suitability versus fish density for fallfish.

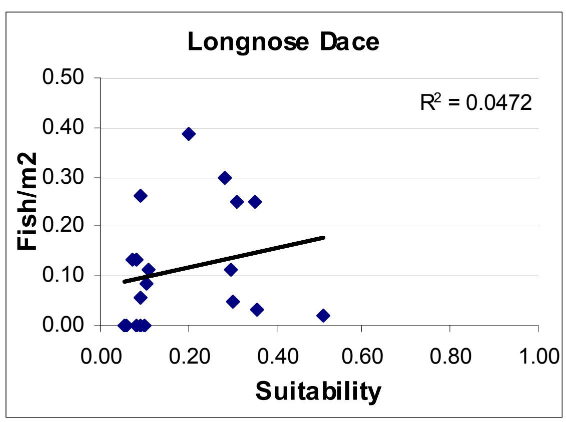

Figure 5: Predicted suitability versus fish density for longnose dace.

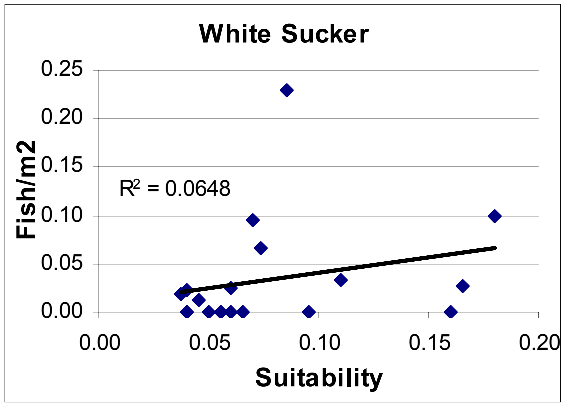

Figure 6: Predicted suitability versus fish density for white sucker.

In Figure 2A for blacknose dace it becomes apparent that there are three high density fish catches that are significantly different than the cluster of other values. These three samples are from three adjacent HMUs, numbers 30002, 30003, and 40001. These sites each captured large schools of BND in the relatively few grids placed within those sites, and therefore resulted in deceivingly high fish densities. After removing these data the correlation between habitat predictions and fish density increased significantly (Figure 2B). There is no positive correlation between the predicted common shiner suitability and fish density. We feel that these data should be removed in the validation process for two significant reasons. First, our model for CS is not yet perfected. Our previous work on rivers in the northeast included low densities of CS and they appeared in less than 10% of the sampled grids. The accuracy logistic regression model is affected by these low densities and our criteria for habitat specifications are weak. Secondly CS was found in the electro-fished grids in only seven habitats in one mapping site and here it was often found in high densities due to schooling. Because of these two conditions we have decided to continue with the validation without the common shiner data. The other species FF, LND and WS have a positive relationship in the predicted habitat suitability versus observed fish/m^2.

The following figures represent the summarized model verification based on the electro-fished grids for GRAF. Figure 7 shows the sum of average probabilities for the fish species: BND, FF, LND, and WS plotted against the sum of fish densities for those species, with the outliers removed. These data show a good correlation, where an increase in sum average probability corresponds with an increase in sum fish density.

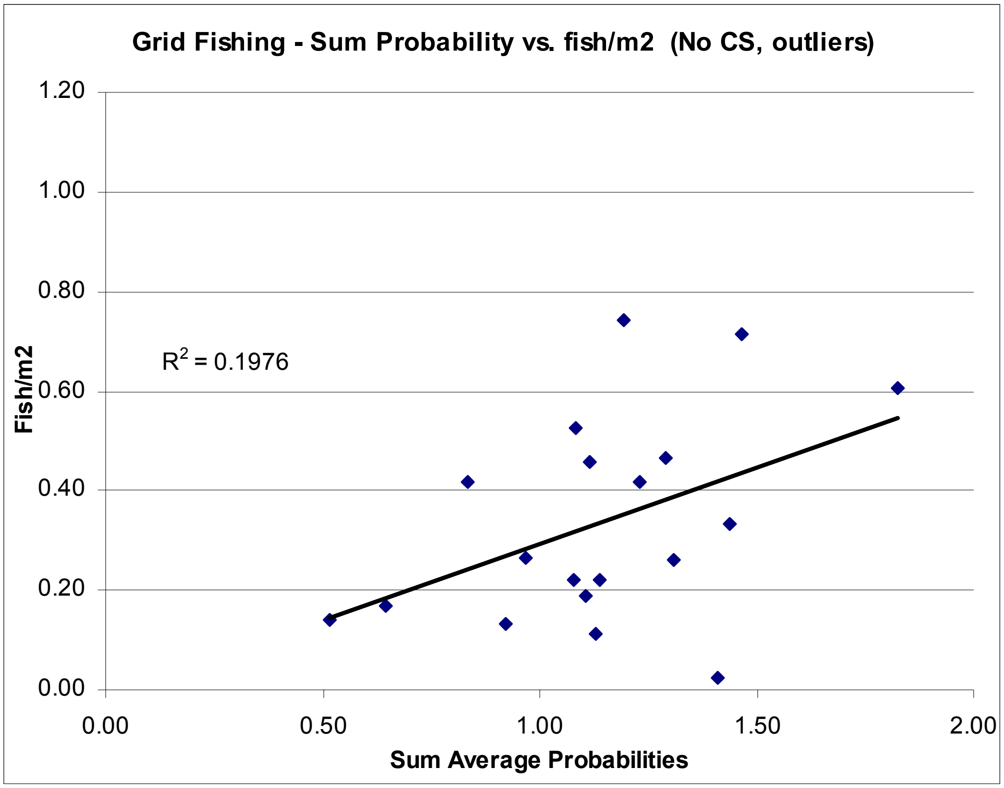

Figure 7: Average probabilities versus sum of fish densities for blacknose dace, longnose dace, fallfish and white sucker.

In the Figure 8, we can examine the predicted suitability category and observed fish density for each fish species except for common shiner at every sampled HMU, excluding the outliers. When we plot the predicted category against the sampled fish density in each HMU we can observe a general trend where HMUs that were predicted to have largely unsuitable habitat in fact contained low sampled fish densities while those predicted to be suitable and very good contained a wider range, but generally a higher density of sampled fish.

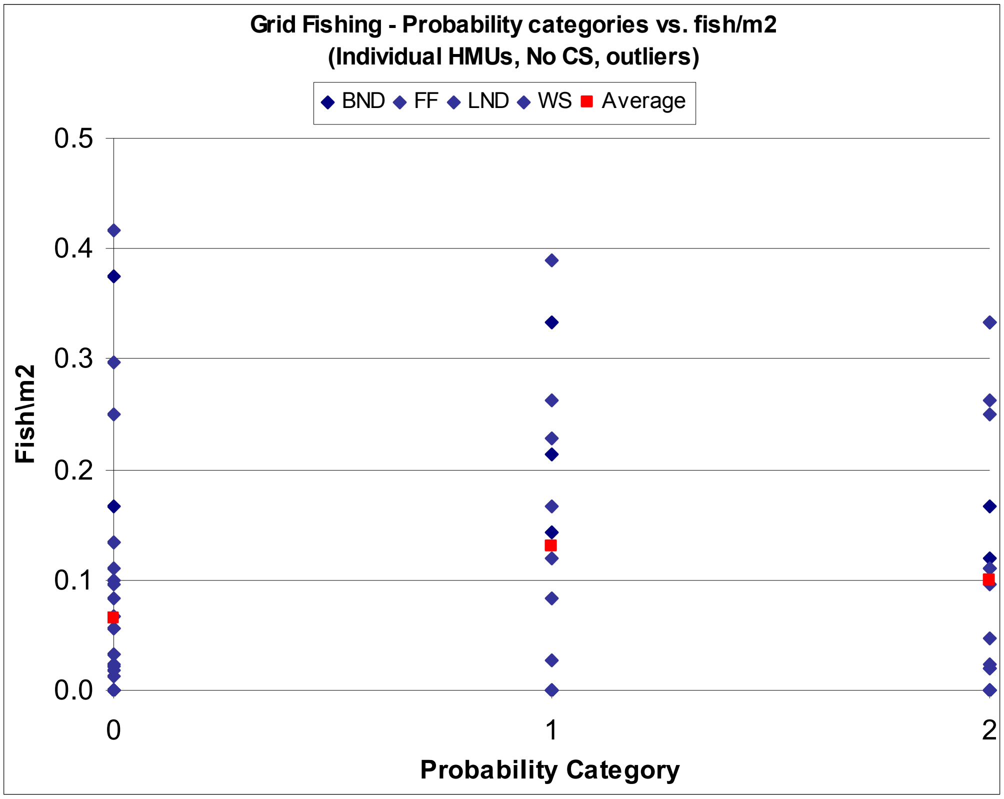

Figure 8: Predicted suitability class versus fish density for blacknose dace, fallfish, longnose dace and white sucker. Averages are shown in red.

Verification of transferability by snorkeling

Data presented in the following graphs uses suitability probabilities calculated for the HMUs mapped during the Habitat Mapping Survey. During the snorkel survey changes in HMU type were noted while fish counts were conducted. Later in the lab we correlated the noted changes and general sequence of HMUs with the HMU mapping conducted under the closest possible flow conditions. The data collected during those closest flow mappings were used to calculate the suitability probabilities. We calculated observed fish densities here by dividing the total fish seen in the HMU with the HMU's area. While we recognize that it was not possible to visually inspect the entire HMU, we strived to have a similar proportion of each unit viewed throughout the survey.

The cross-correlation analysis of data obtained with snorkeling in 37 HMUs does not verify the overall model predictability ($p>0.05$). As presented in Figure 9 the distributions of areas with fish and without fish among habitat classes do not differ significantly. Nevertheless we conducted more detailed analysis of these data using correlation at the species level.

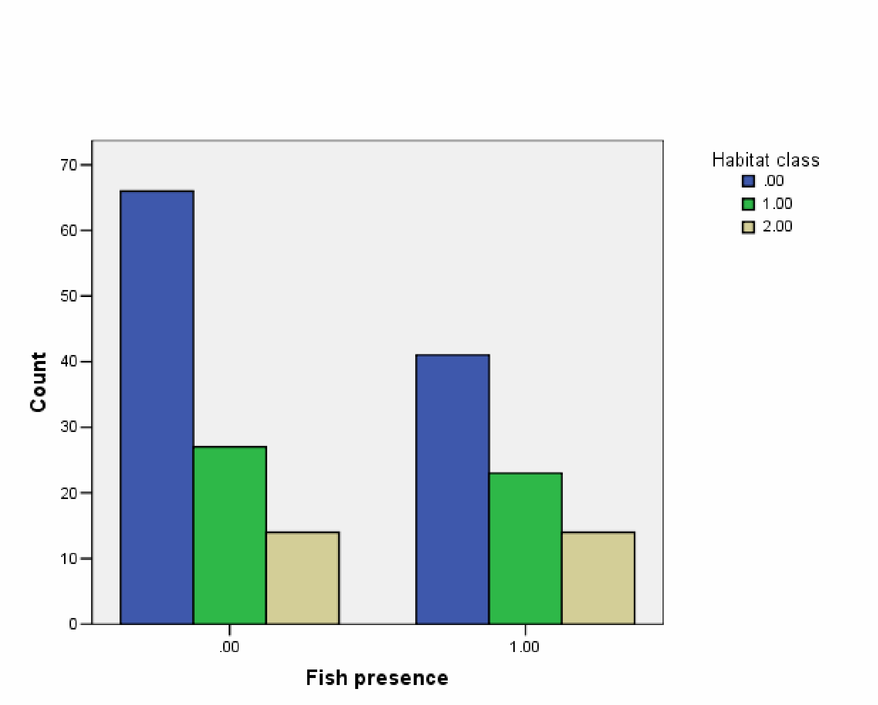

Figure 9: The number of HMUs where fish were present (1) in three habitat suitability categories: unsuitable (0), suitable but not optimal (1), optimal (2).

Predicted suitability was plotted against caught fish densities for the species: BND, CS, LND, FF and WS. The graphs shown below include all surveyed HMUs that were snorkeled for fish identification purposes.

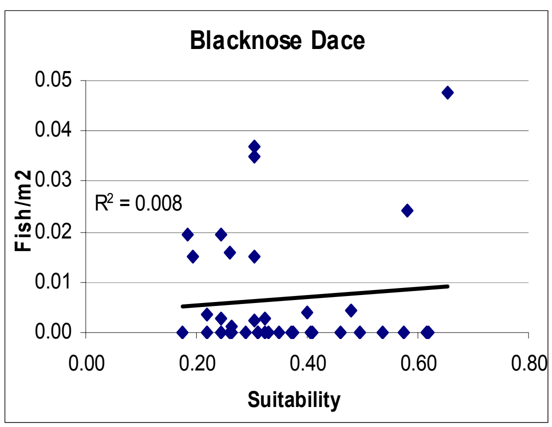

Figure 10: Predicted suitability versus caught fish density for blacknose dace.

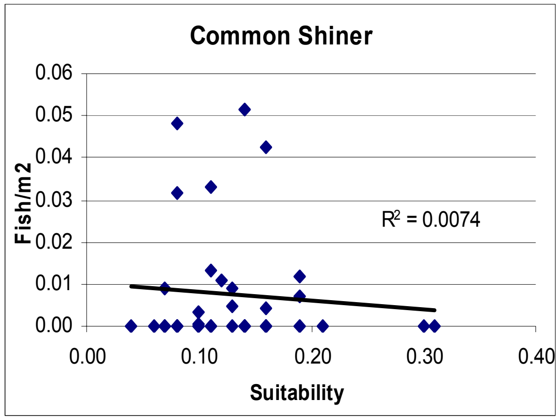

Figure 11: Predicted suitability versus caught fish density for common shiner.

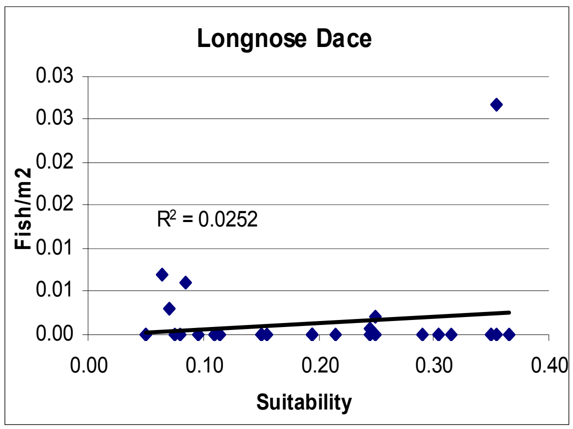

Figure 12: Predicted suitability versus caught fish density for longnose dace.

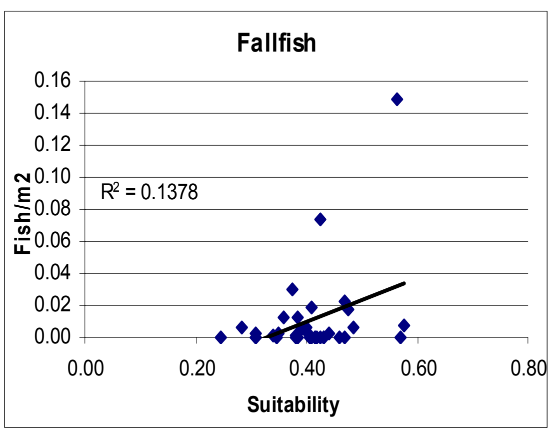

Figure 13: Predicted suitability versus caught fish density for fallfish.

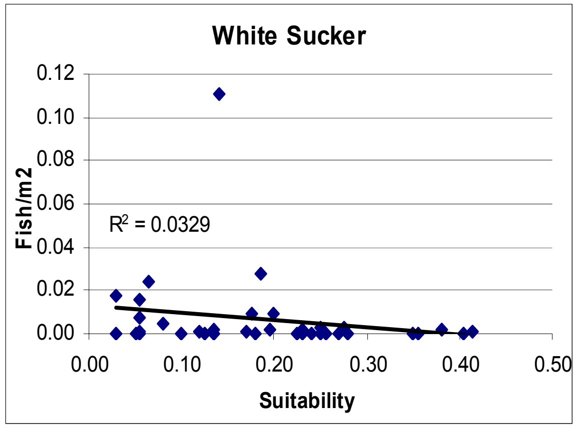

Figure 14: Predicted suitability versus caught fish density for white sucker.

In the five species graphs developed from the snorkeled HMU data it appears that blacknose dace, fallfish, and longnose dace all have positively correlating models. The model for common shiner, as expected from the grid fishing discussion, is too weak to adequately delineate habitat. Because the number of fish observed here was much higher than in the Upper Souhegan the removal of this species from further verification of the model could not be justified. One surprise is the slightly negative relationship in the predicted white sucker data. It is unclear at this time why the model didn't work in the snorkeled HMUs, but it may be related to something inherent to the technique of data collection.

Figure 15 (shown below), compares the sum of average probabilities for each fish species examined (BND, CS, FF, LND, and WS) plotted against the sum of fish densities for those species. As expected no correlation can be documented for these data, however it is apparent that slightly more fish could be seen at the areas with higher probability.

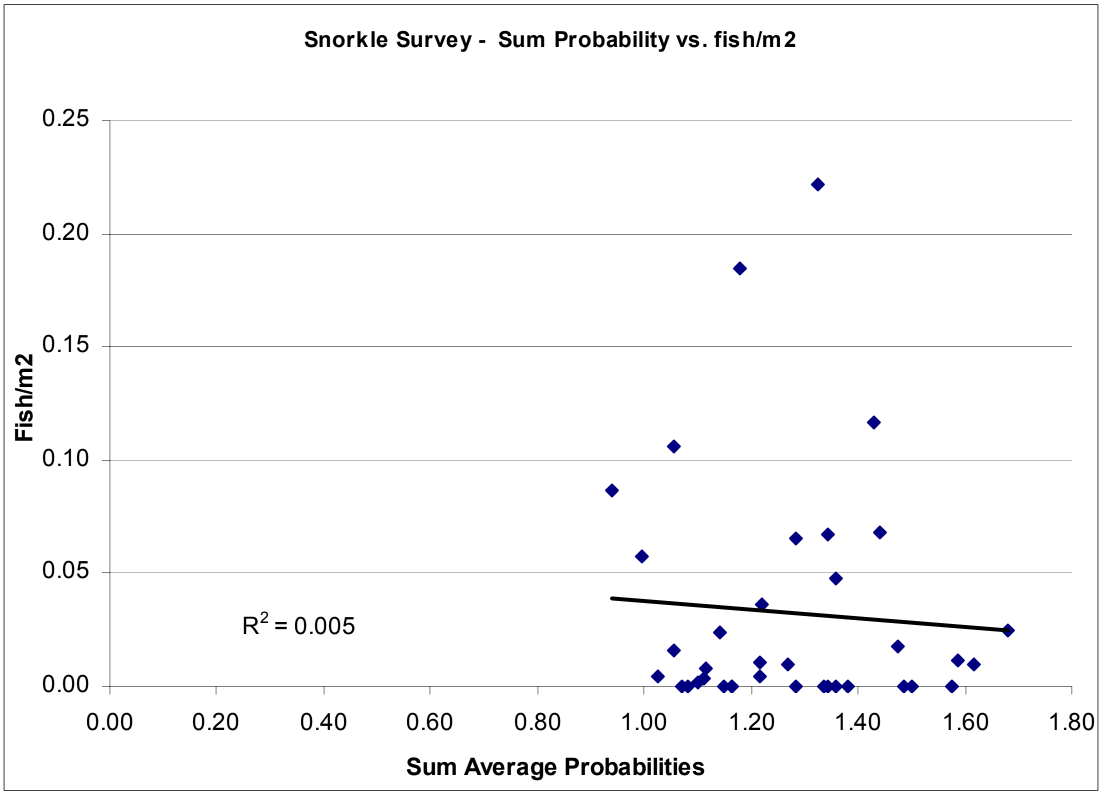

Figure 15: Sum of average probabilities for blacknose dace, common shiner, fallfish, longnose dace and white sucker

In Figure 16 we look at the predicted suitability category and observed fish density for each fish species at every sampled HMU. All the data for the suitability category would therefore fall into the three category scheme. We are looking for categories 1 and 2 to generally have higher observed fish densities. At first glance this graph is again not very convincing because of several high, sampled fish densities in the unsuitable habitat class. However, there appears to be a trend of higher classes having higher fish densities and mean values are also slightly higher.

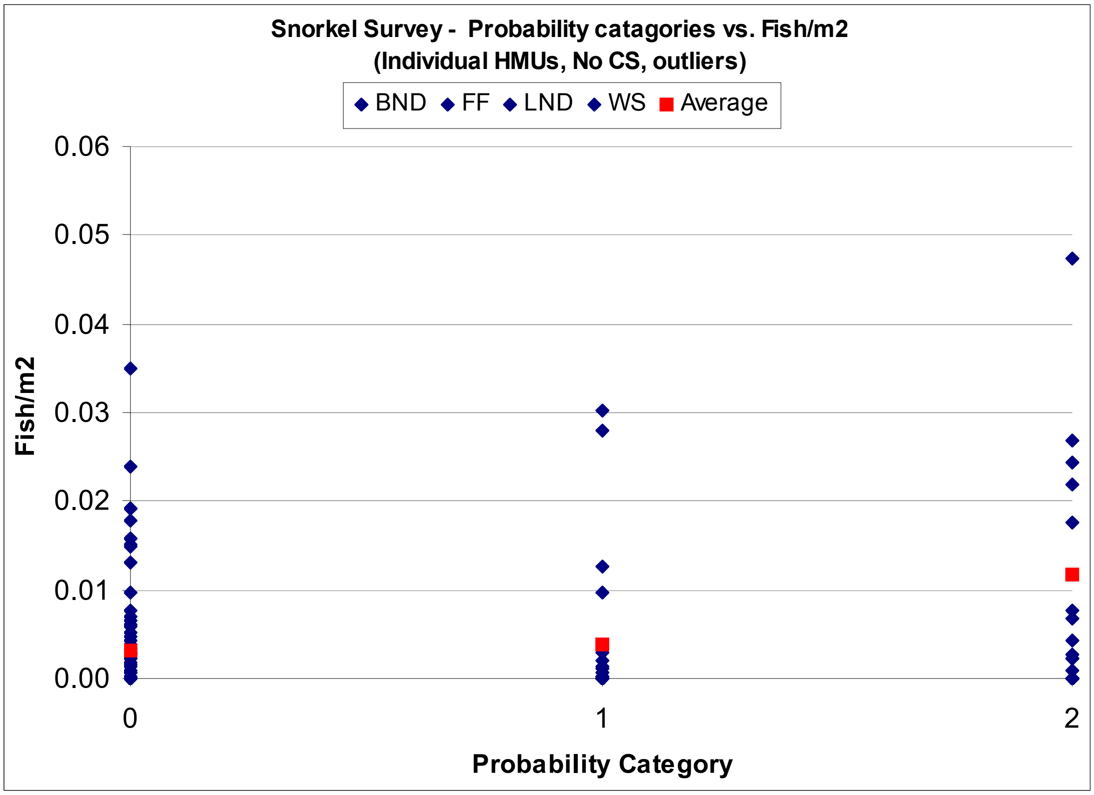

Figure 16: Predicted suitability class versus fish density for blacknose dace, fallfish, longnose dace and white sucker. Averages are shown in red.

Discussion

The model verification provides noisy but satisfying results for data collected using electrofishing, but it does not verify the model transferability with snorkeling. Because MesoHABSIM has been already verified earlier with help of electrofishing we believe that the failure of snorkeling verification is much more due to our sampling inaccuracies than model inadequacy. The area estimates for HMUs used to compute fish density were inaccurate and hampered model performance. Therefore we propose to repeat the snorkeling survey with a modified and more rigorous sampling protocol, using a catch-per-unit-effort rather than area based densities as a measure of habitat use intensity.

At the species level, with the exception of common shiner all the models have significant positive correlations with fish data. Although there is a clear increase in numbers of captured fish with increasing probability, the R^2 values are very low for most of them. This is not surprising, as suggested by Cade & Noon (2003), the habitat models encompass only a portion of the factors influencing fish behavior. Due to the use of quantile regression, proposed by the same authors, it is likely to be a more precise method than the ones applied here. The pattern in Figure 16 also indicates that in areas where we found more fish, the increase of fish density corresponds with the increase of predicted habitat suitability.

As for the snorkeling data, the only meaningful relationship that could be established was for fallfish and to limited extent for blacknose dace. Both species are best represented in the data set used for computing of habitat suitability criteria and have therefore the most precise models.